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Energy Saving Potential, Costs and Uncertainties in the Industry: A Case Study of the Chemical Industry in Germany

Fabian Bühler [a], Andrej Guminski [b], Anna Gruber [b], Serafin von Roon [b] and Brian Elmegaard [a]

[a] *Technical University of Denmark, Kgs. Lyngby, Denmark, fabuhl@mek.dtu.dk.*
[b] *Forschungsgesellschaft für Energiewirtschaft mbH, München, Germany, aguminski@ffe.de.*

Abstract:

In Germany, 19.6 % of the industrial final energy consumption (FEC) can be allocated to the chemical industry. Energy efficiency measures with focus on the chemical industry could thus significantly contribute to reaching the German goal of reducing greenhouse gas emissions by 80 % in 2050 compared to 1990. To achieve this ambitious goal, energy planners and industries alike require an overview of the existing energy efficiency measures, their technical potential as well as the costs for realizing this potential. Energy efficiency opportunities are commonly presented in marginal cost curves (MCCs), which rank these measures according to specific implementation costs. Existing analyses, however, often do not take uncertainties in costs and potentials into account. The aim of this paper is to create a MCC of energy efficiency measures for the chemical industry in Germany, while quantifying the uncertainties of the results and identifying the most influential input parameters. The identification of energy efficiency measures and the quantification of the associated technical potentials and costs are identified based on literature data and own assessments. Based on these findings, a cost curve is created for the current technical potential. To investigate the uncertainties of the model output, Monte Carlo (MC) simulations are performed to quantify the standard deviations of the implementation potential and costs. Furthermore, a sensitivity analysis, based on Morris Screening and a linear regression, is conducted in order to identify the most influential model input parameters.

Keywords:

Energy Efficiency, Chemical Industry, Marginal Cost Curve, Uncertainty, Sensitivity Analysis.

1. Introduction

In Germany, 19.6 % of the industrial final energy consumption (FEC) could be allocated to the basic chemical industry in 2014 [1]. For the year 2014 the annual energy related greenhouse gas (GHG) emissions were approximately 47.6 Mt CO_2eq. [2]. GHG abatement measures with focus on the chemical industry, could thus significantly contribute to reaching the German goal of reducing these emissions by 80 % to 95 % in 2050 compared to 1990. To achieve this ambitious goal, the quantification of abatement opportunities and their individual costs has great significance for energy planners, industries and governmental institutions. In addition, a robust representation of the industrial sector in national or regional energy system models is needed to obtain accurate results for scenario analyses and forecasts.

A detailed analysis of the German industry as a whole is performed by Fleitner et al. [3]. The authors first distribute the FEC and GHG emissions of the industry to different subsectors. Then, a variety of scenarios showing the energy and GHG reduction potential are calculated for the largest industrial sectors. The chemical industry in Germany is described in detail including the main basic chemicals. The results show a technical reduction in FEC of 14 % until the year 2035, with respect to the base year 2007. Furthermore, the study elaborates that most measures are economically feasible. The economic potential is only 1 %-point lower than the total technical potential.

Saygin et al. [4] analyse the impact of uncertainties in FEC and production data on long term energy efficiency assessments. The paper provides a detailed analysis of the basic chemical industry in

Germany. The analysis quantifies the annual energy efficiency improvements. Limits of the calculations, due to the availability of FEC and production data, are discussed.

An analysis of energy efficiency opportunities in the German pulp and paper industry is found in [5]. The authors determine energy consumption on a process level and establish 17 energy efficiency measures. Several scenarios for the implementation until 2035 are analysed and a sensitivity analysis for the CO_2 Abatement Cost Curve is provided. The sensitivity analysis takes into account the discount rate and the selected year of implementation. A higher discount rate was found to increase the costs, whereas selecting an implementation year that lies further in the future, increases the potential and reduces the costs of implementation of energy efficiency measures, due to technology diffusion.

Kesicki and Ekins [6], highlight several shortcomings of using marginal abatement curves to illustrate climate change mitigation options. Several limitations are linked to the static nature of the MCC. While the MCC is a useful tool to communicate an overview of the potential of climate change mitigation options and the associated costs of implementation, it fails to address intertemporal dynamics and possible interdependencies between individual measures. Another methodological shortcoming is the lack of uncertainty analysis. Furthermore, Kesicki [7] combines MCCs with energy system models, thereby overcoming shortcomings such as technological potential, system wide interactions and uncertainties. The author highlights the importance of conducting an uncertainty analysis for input parameters, such as fuel prices and technologic deployment, by listing it as an idea for future research.

This paper aims at analysing the chemical industry from an energy perspective and at quantifying the potential for energy efficiency measures. The potential for a reduction in FEC is quantified for the basic chemical industry and implementation costs for individual measures are determined. This paper focuses on the implementation of measures leading to process and equipment optimisation. Cross sectional technologies (such as pumps, air condition and lightning) and fuel switch measures are not considered.

The sectoral analyses are subject to a high degree of uncertainty. This is due to the fact that these analyses rely on literature data, which may vary between sources, and expert interviews that are subject to individual views and assumptions. In this paper, the effect of these uncertainties is quantified using a strict methodical approach. By conducting an uncertainty analysis, the most influential input parameters are identified. The latter are subsequently altered in a sensitivity analysis, to show the effect on the model output. Hence, by performing an uncertainty and subsequent sensitivity analysis possible inaccuracies in the underlying data are addressed and the effects on the results are quantified. This increases the interpretability of the results and partially alleviates the shortcomings of the MCC approach.

The overall aim of this paper is to construct a MCC of energy efficiency measures for the basic chemical industry in Germany and to quantify the effects of uncertain data and sensitive model results on the order of measures in the MCC. To achieve this goal, the following steps are performed for the basic chemical industry in Germany:

(i) Analysis of the FEC

(ii) Determination of possible energy efficiency measures

(iii) Determination of potential energy savings and the associate implementation costs

(iv) Quantification of the uncertainties of the results and identification of the most important model parameters

2. Method

In this section, the methods and assumptions used to construct the MCC of energy efficiency measures in the chemical industry are introduced. First, the approach for modelling the FEC in the chemical industry is described. Then, possible energy efficiency measures are determined and the method used to determine specific energy saving potentials and costs for the implementation of selected measures is defined. The concept of marginal cost curves is explained in section 2.3. Ultimately, the methods used in the uncertainty and sensitivity analyses are described.

2.1. Energy Modelling of the Chemical Industry

In this work, a top down approach is used to model FEC in the chemical industry. First, total FEC for the production of basic chemicals is divided by sub-sectors. Then, FEC by product is further disaggregated to the production process level. This step is performed for products that can be produced via more than one production route. The resulting FEC by product and production process builds the basis for selecting the most energy intensive processes, which are subsequently analysed with regard to potential energy savings. The sub-division is based on literature data such as [3,8–10] and is visualised in figure 1.

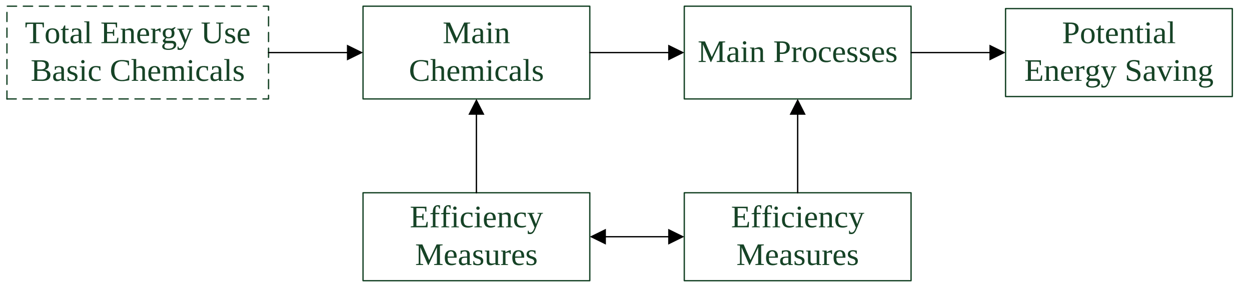

Fig. 1. Overview of the modelling approach for the chemical industry.

Based on the analysis of FEC data in the chemical industry, ammonia, ethylene, methanol, chlorine and polyethylene and the according production processes are considered for further analysis.

2.2. Energy Efficiency Measures

In the following, the selection and evaluation procedures for energy efficiency measures are described. The most relevant and applicable energy efficiency measures for the chemical industry in Germany are identified based on a literature review and expert assessments. An overview of the measures and the quantification of their potentials and costs can be found in section 3.

Three types of measures are considered: (i) bundled measures, which can be applied to the entire production site (ii) bundled measures, which can be applied to a specific process or (iii) specific measures, with a high implementation potential. In (i) and (ii) several individual measures are combined to form measure bundles. Measures within a bundle might be subject to interdependencies. Hence, it is possible that not all measures within a bundle can be implemented fully. Furthermore, depending on site specific parameters, some measures might already be in use. As interdependencies have already been accounted for within the bundle, it is possible to apply them to the complete subsector. Lastly, also specific measures are analysed, which describe the complete replacement of current production processes.

All three types of measures are associated with specific energy savings, an applicability factor as well as capital expenditure (CAPEX) and operating expenditure (OPEX). CAPEX are derived from specific investments per energy unit saved or the annual production capacity. CAPEX are annualized using the annuity factor, AF, which is calculated using expression (1). The annuity factor takes into account the expected rate of return on invested capital, *n*, and the interest rate, *i*, which are set to 10 years and 5 %, respectively. Ultimately, investments are corrected for inflation, with the base year being 2007.

$$\mathrm{AF} = \frac{\mathrm{i}}{1-(1+i)^{(-n)}} \tag{1}$$

The energy saving potential, the required CAPEX and OPEX are identified for each measure. Subsequently the potential monetary savings, resulting from the implementation of the measure, are determined. The boiler efficiency, η_{Boiler}, is assumed to be constant at 90 % and the price for natural gas, c_{gas}, is set to 0.025 € per kWh. Annual fuel savings are calculated based on equation (2), where E_{Saved} is the energy saved due to the implementation of a given measure. If the implementation of a measure results in electricity savings, an electricity price of 0.05 € per kWh is used and can be directly multiplied with E_{Saved}. Energy savings and expenses are treated as real annual savings or expenses and are therefore not discounted.

$$\text{Savings Natural Gas} \, [\text{€ year}^{-1}] = E_{\text{Saved}} \times \frac{1}{\eta_{\text{Boiler}}} \times c_{\text{gas}} \tag{2}$$

The specific monetary savings or expenses of each measure are calculated using equation (3).

$$\text{Specific Costs} \, [\text{€ GJ}^{-1}] = \frac{\text{CAPEX} \times \text{AF} - (\text{Savings} - \text{OPEX})}{Q_{\text{Saved}}} \tag{3}$$

Costs are presented as annualized specific savings to allow for comparisons amongst a heterogeneous set of energy efficiency measures and for a given year. This paper assumes that the analysed measures are implemented instantaneously. The realized monetary savings and energy efficiency potential consequently does not vary over time.

2.2.1. System Boundaries and Assumptions

The analysed systems include processes, which are used to produce the primary product. Processes used to refine the final product as well as by-products are not considered. Furthermore, the measures aimed at reducing fuel used as feedstock are excluded from the analysis.

Some of the analysed energy efficiency measures can only be applied to a specific production step, whereby some are applied to the entire factory. Cross sectional technologies, such as compressors, boilers and motors, are not considered.

It is assumed that all process fuels are used to produce process steam in boilers with an average efficiency of 90 %. Unit prices for fuels are identical for all sub-sectors and constant over time. The results do not distinguish between electrical energy and fuel savings. However, across all sub-sectors, with the exception of Chlorine, the fuel energy input accounted for the highest share of energy input. In the chlorine production, electricity is the major source of energy.

Furthermore, investment cycles of 20 years and 50 years are assumed for investments in energy efficiency measures and complete changes of the production processes, respectively.

2.3. Marginal Cost Curves

Marginal cost curves are a tool to compare different opportunities to reach a potential target.

The comparison and analysis of energy saving measures using marginal cost curves is explained in [11]. Each block depicted in the MCC represents a specific measure or measure bundle. The specific costs for implementing energy efficiency measures are shown on the ordinate axis. Negative costs imply specific savings; positive values can be interpreted as additional costs imposed due to the implementation of a given measure. The abscissa axis represents the total potential for reducing the energy consumption for a given year. The width of each block in the MCC is contingent upon the technical energy savings potential and the applicability of a given measure.

2.4. Uncertainty and Sensitivity

The sectoral energy analysis and energy efficiency measures are connected to several sources of uncertainty. Variations of the potential energy savings and the costs of the measures can have a significant impact on the shape of the MCC and thus analysed in more detail. As this work relies on assumptions and literature data, which vary amongst sources, quantifying the uncertainty of the results and determining the most important input parameters increases the interpretability of the results.

In this work the uncertainty of the model output is analysed by using the Monte Carlo method [12]. This method determines the probability of the model output based on defined uncertainties of the inputs. Within the input uncertainty space of dimension (N-by-k), random values are generated for each input parameter, where k is the number of parameters and N the number of model evaluations. The sampling of the input space is performed using Latin hypercube sampling (LHS) [13]. The approach of this analysis is based on the work by Sin and Gernaey [14]. The mean, standard deviation and the 95 % percentiles are reported for the results.

In order to identify the most influential model input parameters, Morris Screening [15] is used. Linear regression of the MC simulations is additionally used in this work for the sensitivity analysis to validate the findings. Morris Screening estimates the Elementary Effects for all uncertain input parameters on the model output. First samples are created using Morris sampling, followed by model evaluations. The EE are then determined for each input and the input parameters are ranked according to their mean value and standard deviation. The Morris Screening has three degrees of freedom. The number of levels, p, the number of repetitions, r, and the perturbation factor, Δ, define the level of detail [16], which has to be balanced to the computational time required. The reported screenings used 20 repetitions and 6 levels.

Based on the performed Monte Carlo simulations, linear regression is used to summarise the relationships of the parameters [17,18]. For the linear regression, the Standardized Regression Coefficient (SRC of beta) is used. The SRC can take a value between [-1, 1] for each parameter, describing the magnitude of the influence and if it has a positive or negative effect. The sum of the squared SRC is unity. In order to apply this method, the R^2 of the linear regression model has to be above 0.7. Values above 0.7 indicate that the model could be sufficiently linearized [16].

In order to conduct the uncertainty and sensitivity analyses, the uncertainty input range, as well as its distribution, are defined for each parameter. As described in the previous sections, the main model input parameters for each energy efficiency measure are the energy savings, the applicability to the whole industry, the investment and OM costs, as well as the lifetime of the measure. For several measures, the uncertainties are given in the literature or were defined based on variation found in literature values. If this was not possible due to a lack of data, the uncertainty was set to ±15 % for technical and ±20 % for economic parameters, as an estimate of general uncertainties. A uniform distribution of the uncertainties was chosen.

3. Chemical Industry

In the following section, the considered chemical products and production processes are introduced. First, a brief summary of the overall production processes for the given product is provided. Then a description of the selected efficiency measures is presented. Lastly, all parameters describing the efficiency measures are quantified and the uncertainties are stated.

3.1. Ammonia

In Germany, Ammonia is primarily produced from natural gas using steam reforming and partial oxidation from other hydrocarbons, in particular heavy fuel oil and distillation residues [3]. In the steam reforming process [19], sulphur is first removed from the natural gas and is then put in a primary reformer where steam is added under a high temperatures and pressures (700 °C to 800 °C at 40 bar). In the secondary reformer, air is added. The output consists primarily of hydrogen and carbon monoxide. The following shift transformation takes place at temperatures between 200 °C and 400 °C, where carbon monoxide is transformed to carbon dioxide and hydrogen. From the mixture, the carbon dioxide is removed. The small fraction of remaining carbon dioxide is converted to methane to ensure no carbon dioxide is present to harm the catalysts. After compression of the syngas, the ammonia synthesis takes place, wherein nitrogen and hydrogen react exothermally to ammonia. When using hydrocarbons, other than natural gas, the first reformers are replaced by gasifier using oxygen as a gasification agent. Sulphur is then removed from the produced syngas. Then carbon dioxide is removed and nitrogen is added.

For the production of ammonia, many process specific energy efficiency opportunities are available [3,19]. Improvements of the reforming process have a high potential to reduce the energy consumption. Possible process improvements are the integration of gas turbines and the replacement of existing gas turbines used to heat the reformer, or to preheat the hydrocarbon feed and the combustion air [10]. Overall reformer improvements, such as pre-reforming, rearrangement of convection coils and additional heat transfer surfaces, would increase the reformer efficiency. The shift reaction could be improved by using improved and sulphur resistant catalysts, as well as have an isothermal shift reaction. In the CO_2 removal section high energy savings can be achieved with advanced solvents, pressure swing absorption or membranes used to efficiently remove CO_2 from the synthesis gas [20]. The ammonia synthesis itself could be improved by smaller, better and lower pressure catalysts. Overall measures targeting a higher degree of process integration, improved process control and maintenance can further contribute to reduced energy consumption. In Table 1, an overview of the implemented values for five selected measures is shown.

Table 1. Aggregated and quantified energy efficiency measures with the range of uncertainty for the production of Ammonia, based on references [3,10,20]. *Own estimates for uncertainty are marked with (*).*

	Measures	**Energy Savings**	**Applicability**	**Investment**	**O&M**
	[-]	[GJ t^{-1}]	[%]	[€ GJ^{-1}]	[€ GJ^{-1} a^{-1}]
A1	Overall Measures	2.22	20	10	**-**
		U[0.6;3.5]	U[10;30]	U[8.5;11.5]	
A2	Small Reformer Improvements	1.40	20	18	**-**
		U[1.0;1.8]	U[15;25]*	U[15;21]	
A3	Large Reformer Improvements	4.00	10	90	**-**
		U[3.0;5.0]	U[7;13]*	U[75;105]	
A4	Ammonia Synthesis	1.00	25*	25	1
		U[0.5;1.2]*	U[20;30]*	U[19;31]*	U[0.7;1.3]*
A5	CO_2 Removal	0.90	30	15	3
		U[0.4;1.4]	U[28;32]*	U[10;20]	U[2.3;3.7]*

3.2. Ethylene

Ethylene is produced in the cracking process, where the preheated feedstock is mixed with process steam and cracked at temperatures of around 850 °C [21]. The resulting gas mixture is quickly cooled down and afterwards fed to low temperature, high-pressure distillation columns. The condensate produced during the cooling processes contains several by-products; aromatics in particular. In Germany the majority of Ethylene is produced with Naphtha as a resource [3].

For the production of Ethylene, three potential energy efficiency measures are identified based on [3,22–24]. Overall measures include heat recovery and improved process control. Improvements of the steam cracker can result in high savings. Potential measures as part of a revamp of the cracker can include [22,23]: advanced furnace material to reduce coking in the pyrolysis section and thus increasing heat transfer; improved coating and shapes of tubes and coils can act as catalysts and increase ethylene yields; integration of gas turbines to produce steam and gas, where combustion gases can be used for preheating the feedstock. Improving the distillation columns can further reduce the energy input. This could be achieved by Heat Integrated Distillation Columns (HIDiC) and the integration of heat pumps [22–24].

Table 2. Aggregated and quantified energy efficiency measures with the range of uncertainty for the production of Ethylen, based on references [3,22–24]. *Own estimates for uncertainty are marked with (*).*

	Measures [-]	**Energy Savings** [GJ t^{-1}]	**Applicability** [%]	**Investment Costs** [€ GJ^{-1}]	**O&M Costs** [€ GJ^{-1} a^{-1}]
E1	Overall Measures	0.39	20*	9.6	1.5
		U[0.28;0.50]*	U[15;25]*	U[3.2;16]	U[0;2]
E2	Steam Cracker Optimisation	1.14	40	12	5.5
		U[0.98;1.3]*	U[30;50]*	U[10;14]*	U[4.7;6.3]*
E3	Advanced Distillation columns	0.40	20	17.5	2
		U[0.3;0.5]*	U[15;25]*	U[15;20]*	U[1.7;2.3]*

3.3. Methanol

The production of methanol is very similar to ammonia. First, a syngas is produced from natural gas using steam reforming or sludge and other hydrocarbons using partial oxidation. In Germany the majority of the methanol originates from oil based hydrocarbons [3]. The energy efficiency measures are thus assumed to be the same as for ammonia, as production often occurs in integrated plants. The measures given in Table 1 for ammonia are also used for methanol. Exceptions are improvements in the ammonia synthesis.

3.4. Chlorine

Chlorine is produced by electrolysis of sodium chloride solution. Different industrial production processes exist. The main production processes are mercury, diaphragm and membrane cell electrolysis [25]. The mercury cell technique is phased out in Germany, due to the high FEC and mercury emissions [3]. Also, the diaphragm cell technique is being converted to the asbestos free membrane cell technique. An emerging technology is the use of Oxygen-Depolarised Cathodes (ODC) instead of the common metal cathodes in membrane cells [25]. The highest potential for energy efficiency is thus the replacement of old factories using the mercury or diaphragm cell technique to new plants using membranes. It is assumed that all plants will be converted. In addition, the replacement of currently used membranes with ODC or improved membranes can reduce energy consumption in the existing and future plants. As a further measure, the heat recovery and process control of existing plants would lead to further energy savings.

Table 3. Aggregated and quantified energy efficiency measures with the range of uncertainty for the production of Chlorine, based on references [3,24,25]. *Own estimates for uncertainty are marked with (*).*

	Measures [-]	**Energy Savings** [GJ t^{-1}]	**Applicability** [%]	**Investment Costs** [€ GJ^{-1}]	**O&M Costs** [€ GJ^{-1} a^{-1}]
C1	Mercury to	3.54	100	225.83	-
	Membrane	U[3.04;4.04]	-	U[82;369]	
C2	Heat Recovery	0.12	20	3.00	-
		U[0.10;0.14]*	U[15;25]*	U[2.55;3.45]	
C3	Process Control	0.35	20	20.00	2
		U[0.3;0.4]*	U[15;25]*	U[17;23]	U[1.7;2.3]
C4	ODC Membrane	2.97	25	0.75	0.075
		U[2.53;3.42]*	U[15;25]*	U[0.64;0.86]	U[0.064;0.086]
C5	Diaphragm to	0.30	100	0.75	-
	Membrane	U[0.25;0.35]*	-	U[0.64;0.86]	
C6	Improved	0.65	100	1,230	-
	Membrane	U[0.55;0.75]*	-	U[933;1526]	

3.5. Polyethylene

Polyethylene is produced from ethylene. Three main products exist: namely high-, low- and linear low-density polyethylene. The polymerisation of the raw material can occur at high pressures, primarily for low-density polyethylene, or at low pressures with catalysts. Different types of reactors, such as backmix, fluidised bed, tubular or autoclave reactor [3,26]. Besides waste heat recovery and overall measures including process control, static mixer reactors are seen as having a large potential [24]. Static mixer reactors increase heat and mass transfer during polymerisation by improving mixing during varying flow regimes [27].

Table 4. Aggregated and quantified energy efficiency measures with the range of uncertainty for the production of Polyethylene, based on references [3,22–24]. *Own estimates for uncertainty are with a (*).*

	Measures [-]	Energy Savings [GJ t^{-1}]	Applicability [%]	Investment Costs [€ GJ^{-1}]	O&M Costs [€ GJ^{-1} a^{-1}]
P1	Static Mixer Reactor	0.67	22	10	1.96
		U[0.49;0.85]	U[18;26]*	U[8.5;11.5]*	U[1.67;2.25]*
P2	Overall Measures	0.05	20	19	2.45
		U[0.04;0.06]	U[15;25]*	U[16;22]*	U[2.08;2.82]*
P3	Waste Heat Recovery	0.07	20	3	-
		U[0.056;0.084]*	U[15;25]*	U[2.5;3.5]*	

4. Results

In this section, the results of the analysis are shown. First the accumulated results for each chemical and the sector as a whole are presented. A more detailed analysis of the measures can be found in section 4.2, where the MCC for energy savings including uncertainties is shown. The results of the sensitivity analysis are presented at the end of the section.

4.1. Energy efficiency in the Chemical Industry

Based on the total FEC in the chosen sub-sectors for 2007, found in [3], and the potential measures to reduce FEC described in section 3, a possible reduction of 23.8 PJ per year would be possible if all measures were implemented. The total reduction is 7.6 % and shown graphically in Fig. 1. These savings would require investments of almost 2 billion Euro, however most measures can be implemented at negative total costs.

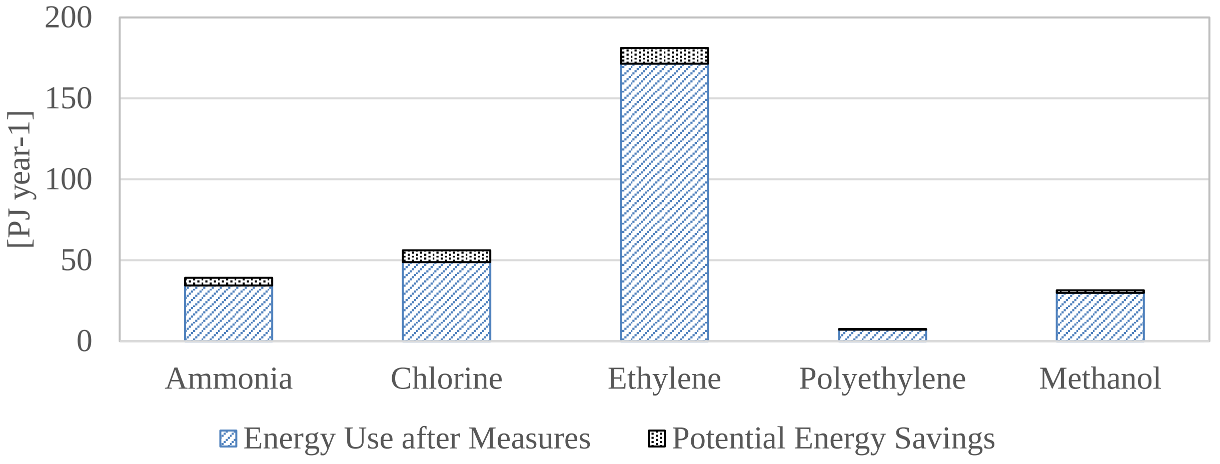

Fig. 1: FEC and energy saving potential for the analysed sub-sectors in the chemical industry.

The results in table 5 show that the implementation of measures in the Chlorine production process results in absolute energy savings of more than 7 PJ per year at specific costs of -6.64 €/GJ. The uncertainty of the energy savings is small, as most improvements result from the replacement of old processes with state-of-the-art equipment. These replacements are very likely to happen, as the industry agreed in revamping of mercury and diaphragm plants containing asbestos [3]. The costs, however, are subject to a higher degree of uncertainty.

Table 5. Summary of the results for each chemical product with the overall uncertainty of the investigated model outputs.

Industry	**Energy Savings** [PJ year^{-1}]		**Specific Costs** [€ GJ^{-1}]	
Ammonia	4.81	± 0.84	-4.58	± 0.81
Ethylene	9.70	± 1.26	-2.26	± 0.78
Chlorine	7.34	± 0.48	-6.64	± 1.81
Methanol	2.12	± 0.47	-3.97	± 0.93
Polyethylene	0.47	± 0.08	-4.93	± 0.69

4.2. Marginal Cost Curve

The MCC for energy efficiency measures in the German chemical industry is shown in Fig. 2. It disaggregates the information presented on the industry-level in Table 5. The mean value and the upper and lower confidence intervals are depicted. Here the confidence interval is defined as the mean value ± standard deviation. It can be seen that the potential is subject to a high degree of uncertainty, while the specific costs have a lower absolute difference across the curve, as the curve changes more in width compared to the heights. Compared to the mean curve, the order of the measures shown in the upper and lower confidence interval curves varies only slightly. This indicates a relatively constant uncertainty of the individual measures. Compared to the mean curve, the order only changes for three measures in the lower bound scenario and for four measures in the upper bound case. When measures change their position in the lower and upper bound, they do so by only moving up to two places away.

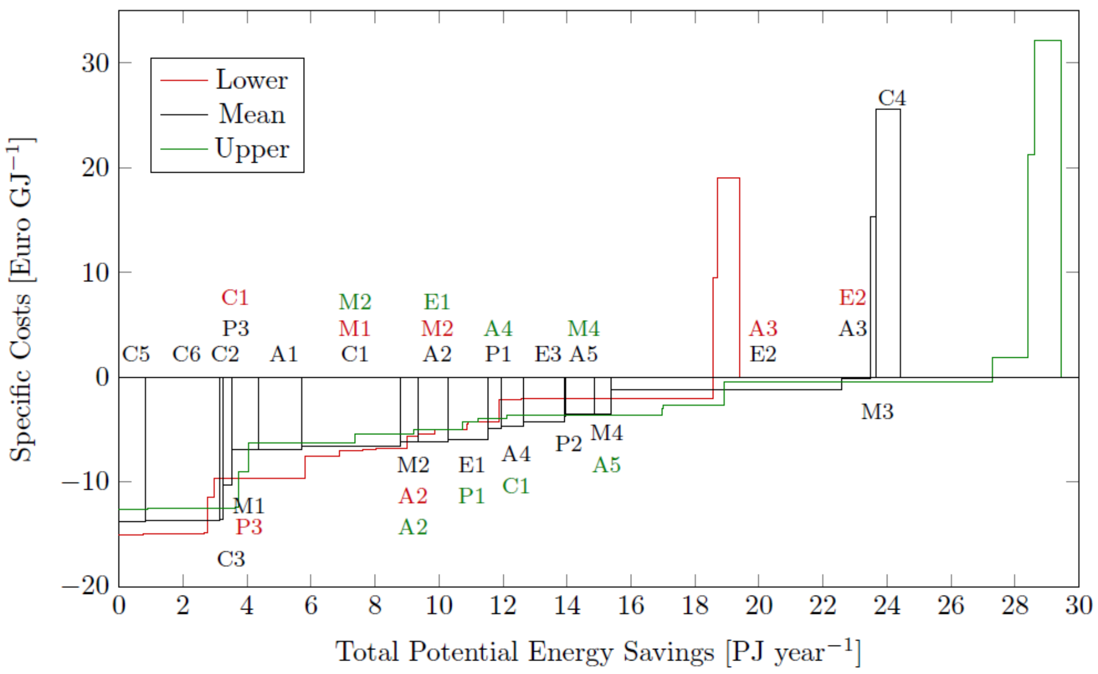

Fig. 2: Marginal Cost Curve of the basic chemical industry with the lower and upper confidence interval. The chosen abbreviated measures given in the figure refer to Table 1- 4.

A more detailed analysis of the MCC is shown in Fig. 3, where only measures with negative specific costs are shown. Furthermore, only the confidence intervals for the specific costs are shown. The curve shows that the uncertainties have a relatively small impact on the curve. Measure C1 and A3 show relatively high uncertainty compared to the other measures. Measure C1 describes the change of the production process for chlorine and measure A3 large improvements of the reformers. Both refer to major production and equipment changes, for which the costs depend on many factors.

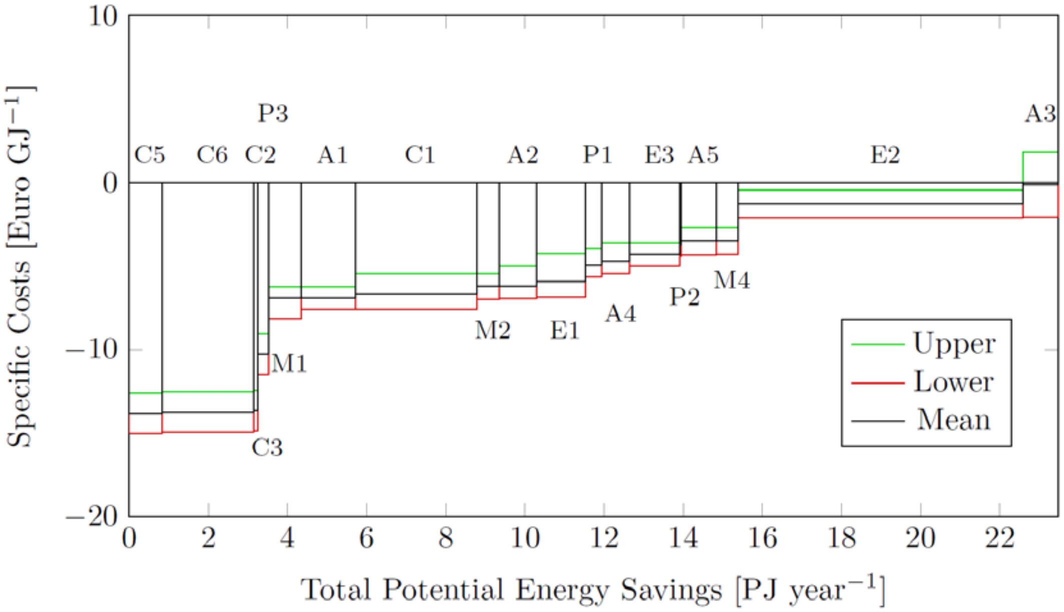

Fig. 3: Marginal Cost Curve with the lower and upper confidence interval for the specific costs. The chosen abbreviated measures given in the figure refer to Table 1- 4.

The total annual savings when implementing all measures is equal to the area under the MCC. For all measures, the total savings are 104 million Euro per year with a standard deviation of ± 20 million Euro. If only measures with negative specific costs are considered, the total savings are 126 million Euro with a standard deviation of ± 19 million Euro.

4.3. Sensitivity Analysis

The sensitivity analysis was performed based on two model outputs. First, the annual possible energy savings are varied. This parameter is selected because it has a high impact on the shape of the MCC. By only considering annual energy savings, the impact of economic parameters is neglected. In order to investigate the impact of energy and economic parameters on the model output, the total possible annual monetary savings are selected as a variable. This model output parameter is the sum of the product of specific costs and annual energy saving potentials for all measures and all subsectors.

The Morris Screening in Fig. 4 is used to identify the input parameters with the highest impact on the energy saving potential of the sub-sectors. The results of the Morris Screening technique are found by comparing the mean and the standard deviations of the distribution function of the EE for each model input parameter [28]. To improve the interpretability of the outcome, the standard deviation divided by the square root of the repetitions is added and subtracted from the mean value. The resulting two lines help interpret the results, as only points lying outside of the cone, have a significant influence on the model output.

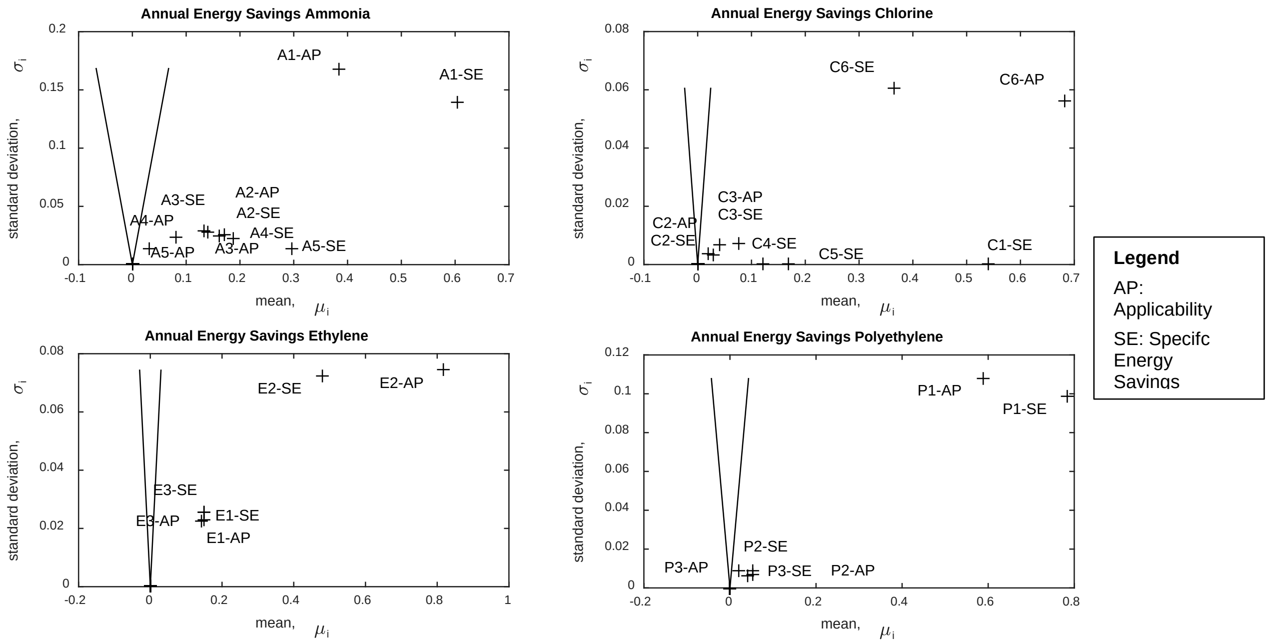

Fig. 4: Sensitivity analysis using Morris Screening for the total annual energy saving potential for each product. The points show the measure from Table 1-4 with the abbreviation of the input parameter found in the legend.

This is useful to refine the most important parameters for the energy system model, where a high number of input parameters are present. It can further be seen that for measures with a high impact, both the applicability and the specific energy savings, contribute significantly to a high deviation from the mean. This is confirmed in the SRC ranking shown in the graphs on left hand side of Fig. 6. In the figure, the influence of parameters is ranked based on the value of their SRC. However, the combination of applicability, AP, and specific energy savings, SE, is not as strict. The model could be linearized to values of R^2 above 0.95 for all results, meaning a sufficient degree of linearisation was obtained.

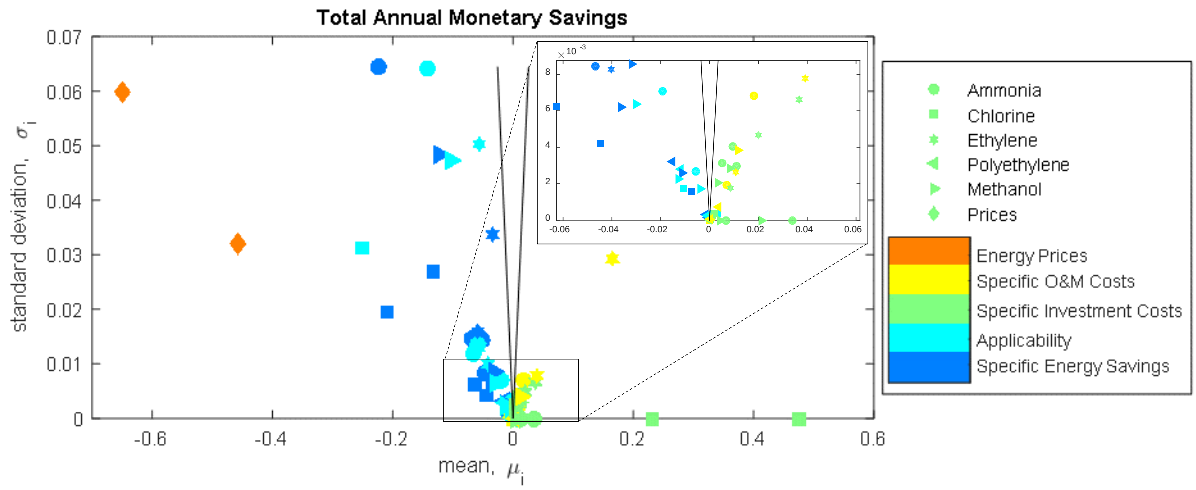

Fig. 5: Sensitivity analysis using Morris Screening of all input parameters on the total annual monetary savings.

Considering the accumulated results across the analysed products and both economic and energy parameters, the dominant input parameters for the uncertainty are shown in Fig. 5 and in the graph on the right hand side of Fig. 6. The Morris Screening shows that energy parameters (SE and AP) have a negative effect and economic parameters have a positive effect. An exception is the energy prices, which also have a negative effect. Furthermore, the energy parameters (blue dots) have a higher impact on the mean model output. These parameters cause a high standard deviation and have a high impact on the mean value. This confirms the observation from the uncertainty analysis of the MCC. The sub-sectors chlorine, ammonia and methanol have the highest impact on the results. However, the majority of the parameters have a small impact on the model output, as they are located around the mean value of 0. This is shown in the zoom out of Fig. 5. Therefore, many of these parameters have a low impact on the standard deviation. This suggests that the model accuracy can be increased by only refining a few influential parameters. As shown in Table 5, the high uncertainty of the specific costs for chlorine is partly caused by savings originating from reduced electricity consumption. In both the Morris Screening and SRC ranking, the electricity price has a considerable influence on the model output. Hereby, the SRC ranking indicates a higher impact than the gas price.

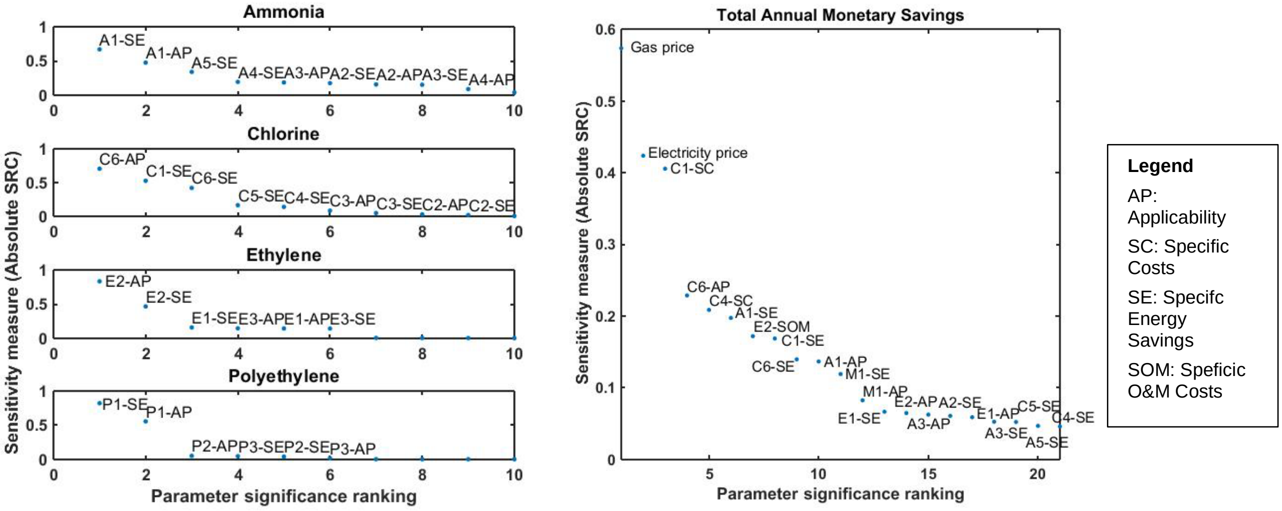

Fig. 6: Sensitivity analysis using linear regression of the annual energy saving potential for each product and the total annual monetary savings. The points show the measure from Table 1-4 with the abbreviation of the input parameter found in the legend.

5. Discussion

The account for the uncertainty of the possible energy savings and their costs by Monte Carlo simulations has been performed. The crucial step in analysing the uncertainty of the model output is the definition and quantification of the model input uncertainty range and its distribution. Uncertainties are not quantified for all literature data, used in this analysis. The missing uncertainty values are estimated based on a comparison of values reported in the literature and own assessments. It is assumed that all input uncertainty ranges are distributed uniformly. This implies that all values within the upper and lower bound have an equal probability to be chosen. As part of future work a comparison of different distribution functions and their impact on the MCC should be performed.

Morris Screening is robust to type II errors (identifying a non-important parameter as important) and SRC is the more precise method, if the model is sufficiently linearized. The combination of the two methods thus allows a better interpretation of the model and the ranking of parameters.

The inflexibility of the MCC with respect to uncertainties has been overcome in this work. The interactions between individual measures are not present in this work, as the measures chosen are independent of each other. However, if cross-sectoral technologies and additional measures are added, these interactions have to be studied in detail.

A refining of the assumptions should be performed, based on the outcome of the sensitivity analysis, better estimating the specific savings obtainable for the most important measures and their applicability to the industry as a whole.

6. Conclusion

This work analysed the energy saving opportunities of the chemical industry in Germany, by considering the costs for implementing energy efficiency measures and their potential. The results are shown in marginal cost curves, where the total potential for implementing the measures are shown, sorted in descending order by their specific costs. It is found that the energy saving potentials for the production of chlorine has the lowest lifetime costs, followed by ammonia and methanol. In total more than 23 PJ of energy use could be saved annually. Most of the measures can be implemented with negative specific costs, meaning that over the equipment lifetime, economic savings from a reduction in FEC outweigh the investment and OPEX. As the analysis is based on estimates and aggregated data from the literature and own assessments, the uncertainty of the model outputs has to be considered. By means of Monte Carlo simulations, the uncertainty for each model output is reported and integrated into the MCC. The order of measures in the MCC is relatively robust. This is a result of assuming uniformly distributed uncertainties. However, it is found that costs and potentials of several measures can have a high impact on the results. Therefore a sensitivity analysis was performed, using Morris Screening and linear regression, to identify the most important model input parameters. It was found that the costs for energy, as well as the specific saving potential and applicability of measures have the highest impact. The Morris Screening and linear regression analysis identified the same important input parameters with small deviations in their order. These can be used to prioritise the refining of input parameters, by expert interviews and detailed assessments.

Nomenclature

a	lifetime [years]
Δ	Perturbation factor [-]
η	efficiency [-]
μ	mean [-]
n	duration [years]
p	perturbation [-]
E	Energy [TJ]
i	interest rate [-]
I	Investment [€]
Q	heat flow [TJ]
σ	standard deviation [-]

Abbreviations

AF	Annuity Factor
AP	Applicability
FEC	Final Energy Consumption
GHG	Greenhouse Gas
MC	Monte Carlo
MCC	Marginal Cost Curve
O&M	Operation and Maintenance
ODC	Oxygen-Depolarised Cathodes
SC	Specific Costs
SE	Specific Energy Saving
SOM	Specific Operation & Maintenance
SRC	Standardized Regression Coefficient

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